Efficient Population-Representative Whole-Cortex Parcellation Based on Tractography

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1 Introduction

The human brain is arranged in areas based on criteria such as cytoarchitecture or extrinsic connectivity. Current hypotheses attribute specialized functions to several areas of this patchwork. Hence, parcellating the cortex into such areas and characterizing their interaction is key to understanding brain function. Diffusion MRI enables the exploration of physical connections through axonal bundles, namely extrinsic connectivity. Current theories hold that brain function is determined by extrinsic connectivity. However, obtaining a population-representative parcellation based on extrinsic connectivity remains challenging (Jbabdi and Behrens, 2013). Particularly, whole-cortex parcellation methods (Moreno-Dominguez et al., 2014; Parisot et al., 2015) are computationally expensive and need tuning of several parameters. Our main contribution is an efficient technique to create single-subject and population-representative parcellations based on tractography. Our method creates a dendrogram using only one parameter: the minimum size of each parcel. Then, by choosing cutting criteria, we can explore different parcellation granularities without recomputing the dendrogram. Experiments show that our extrinsic based parcellations are consistent within subjects with anatomical (Desikan et al., 2006) and functional (Barch et al., 2013) parcellations existent in the literature.

2 Methods

We use 27 males aged 31-35 from the group S500 of the Human Connectome Project (HCP) processed with the minimum pipeline (Glasser et al., 2013).

For each subject we create tractograms using 15000 particles (Behrens et al., 2003). We avoid superficial cortico-cortical fibers (Reveley et al., 2015) by shrinking each surface $3mm$ into the white matter. Once the tractogram of a seed is created, the voxel's value is the odds of being connected to the seed. To compare and average these odds values we transform them into a vectorial space using the logit function (Pohl et al., 2007). This transform allows us to treat tractograms efficiently in a sound mathematical framework.

The proposed transformation allows us to cluster tractograms efficiently. We use as clustering algorithm a modified Agglomerative Hierarchical Clustering (AHC). Since we work in a vectorial space, we use the euclidean distance and the centroid as similarity and linkage functions, improving performance. Finally, to get local coherence (Schmahmann and Pandya, 2006), we add a parameter to constraint the minimum size of the resulting clusters: clusters smaller than this size are only merged with neighbors, i.e. physically close clusters in the cortex. We create each subject's parcellation clustering all of his tractograms. Also, taking advantage of working in a vectorial space and seed correspondence across subjects, we create a population parcellation clustering the population-averaged tractograms of each seed (Figure 1).

3 Results

Figure 2 shows single-subject parcellations using a minimum cluster size of $1mm^2$. Figure 3 (a) shows 9 regions from an anatomical atlas (Desikan et al., 2006) projected over the subject 1

parcellation in Figure 2 and how many of our parcels were contained by those projections. Figure 3 (b) shows the projection of some of subject 1 parcels over functional responses to particular stimuli (Barch et al., 2013). Each color encodes the response to a different stimulus thresholded with a Z-score > 5. To compare them we calculate the Dice coefficient between our parcels and the activations. Several projected parcels have high coefficients with at least one functional response. Figure 4 (a) shows the same as figure 3 (a) for the population clustering of the 27 subjects. Figure 4 (a) shows the same as figure 3 (a) for the population clustering of our 27 subjects. Figure 4 (b) compares our population clustering with average functional responses in the Unrelated100 population from the HCP.

4 Conclusions

Our pure extrinsic based parcellation has good agreement with anatomical and functional parcellations from the literature. Particularly, the motor and sensory cortex appear to be found. Having the tractograms in a vectorial space allowed us to work efficiently with them and to create a population-representative parcellation.

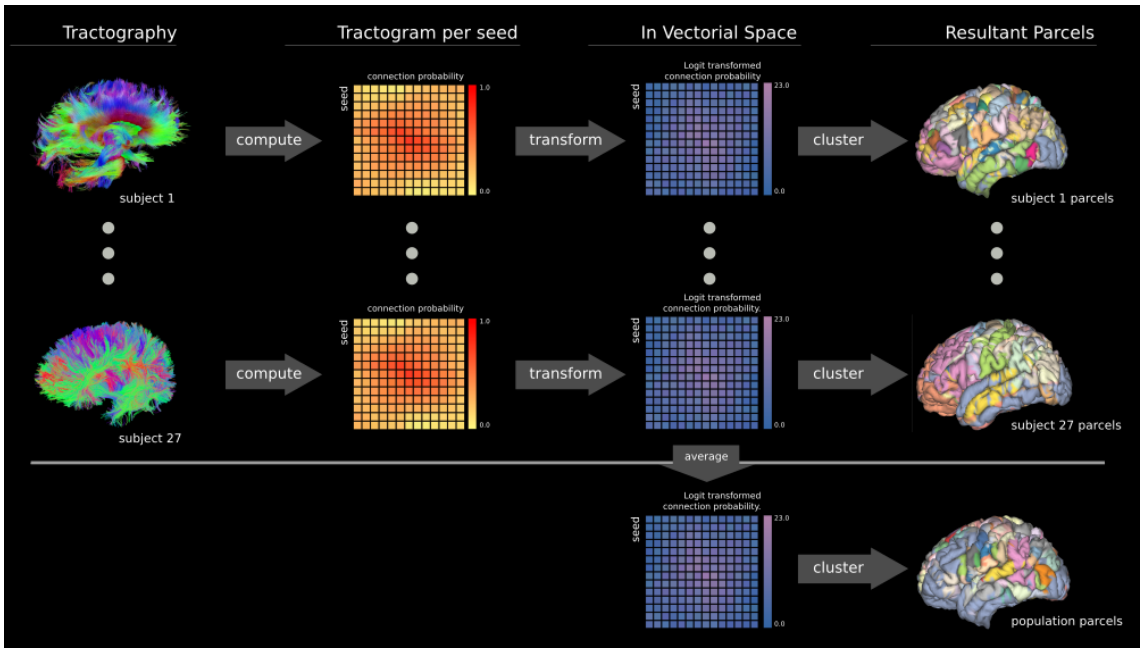

Figure 1: Clustering Process: the tractograms are transformed into a vectorial space where we can manipulate and average them.

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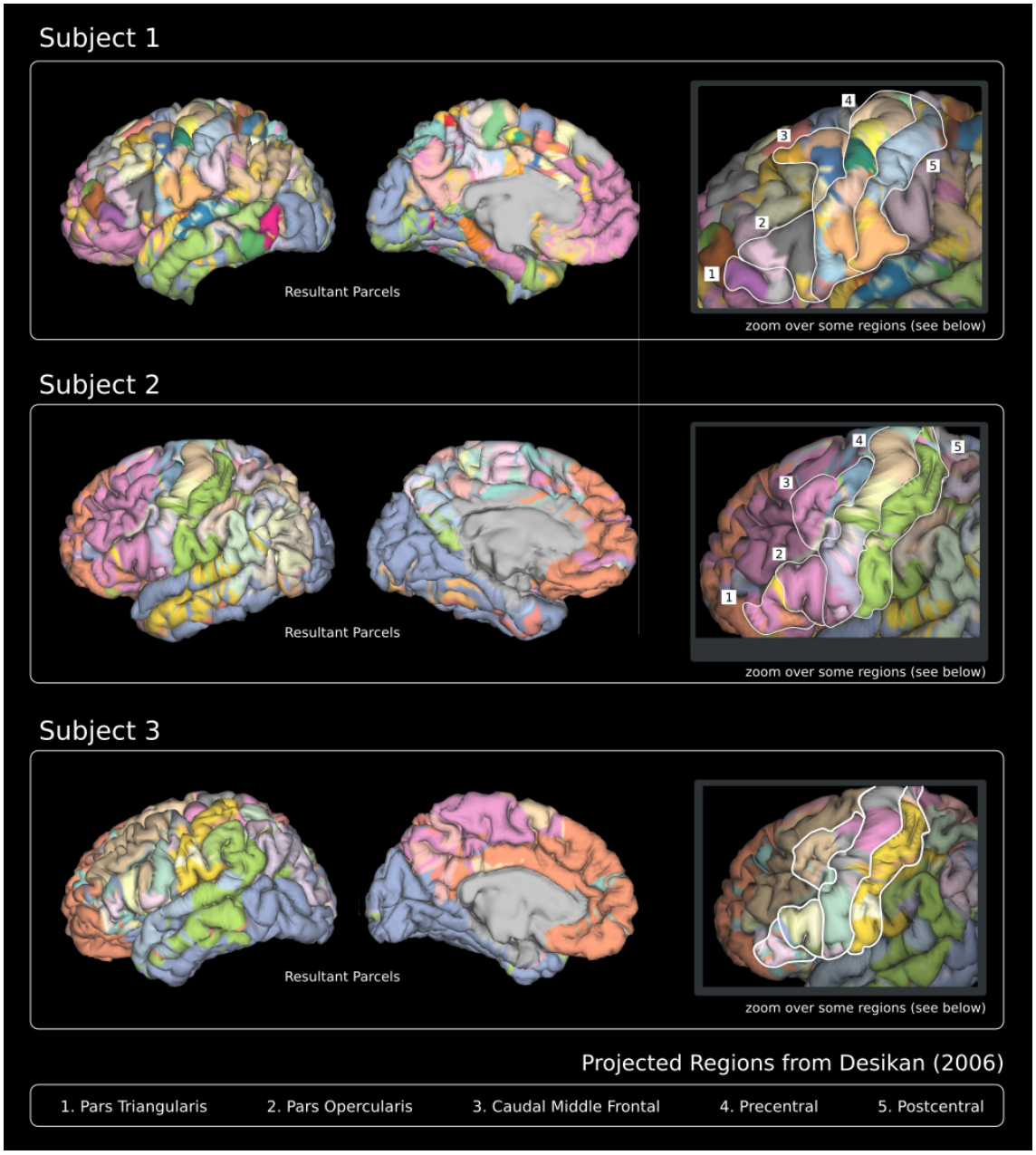

Figure 2: Results for the single-subject case. Some regions from Desikan (2006) appear to be found.

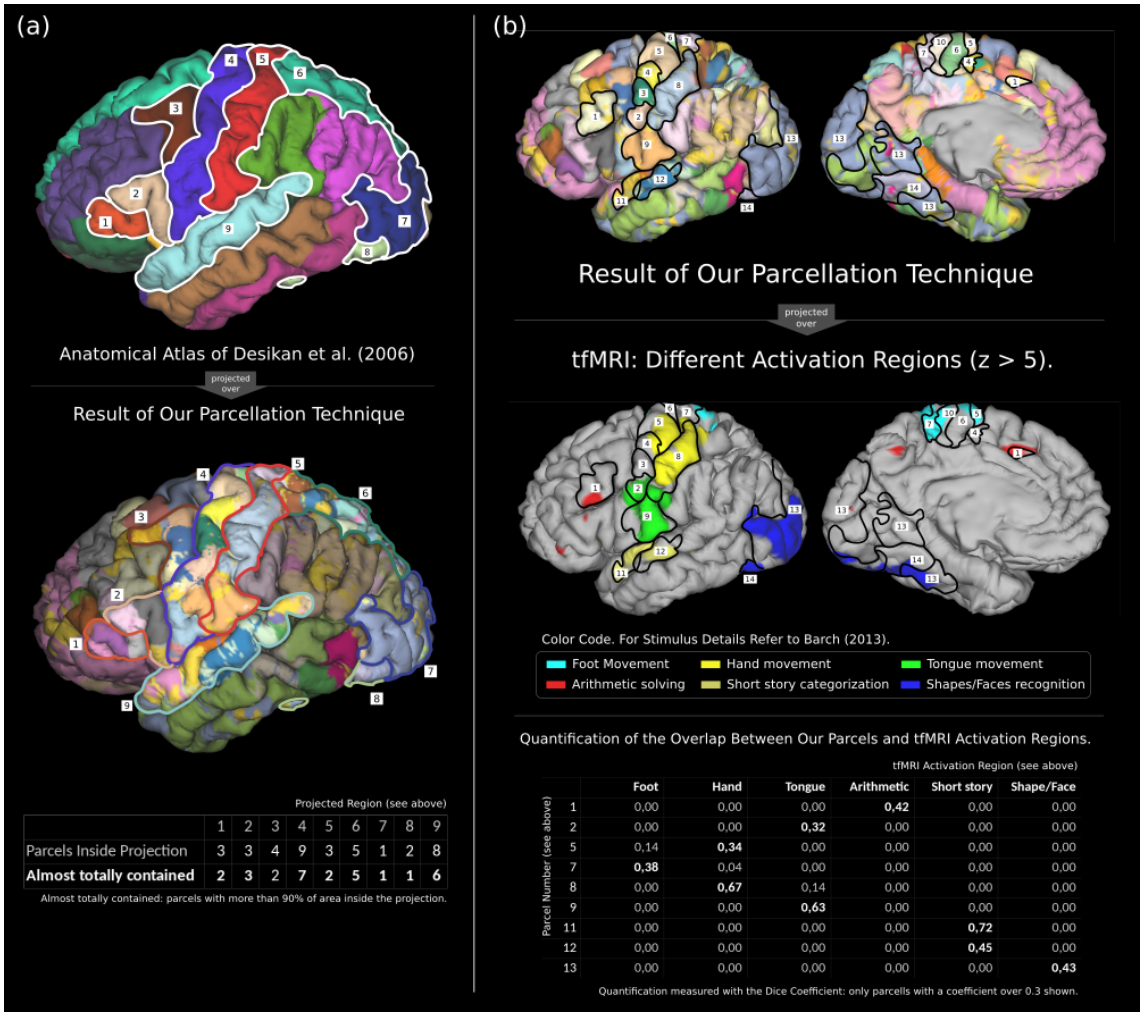

Figure 3: Comparison between our automatic generated parcels; an anatomical atlas (Desikan 2006) and a functional study over the subject (Barch 2013).

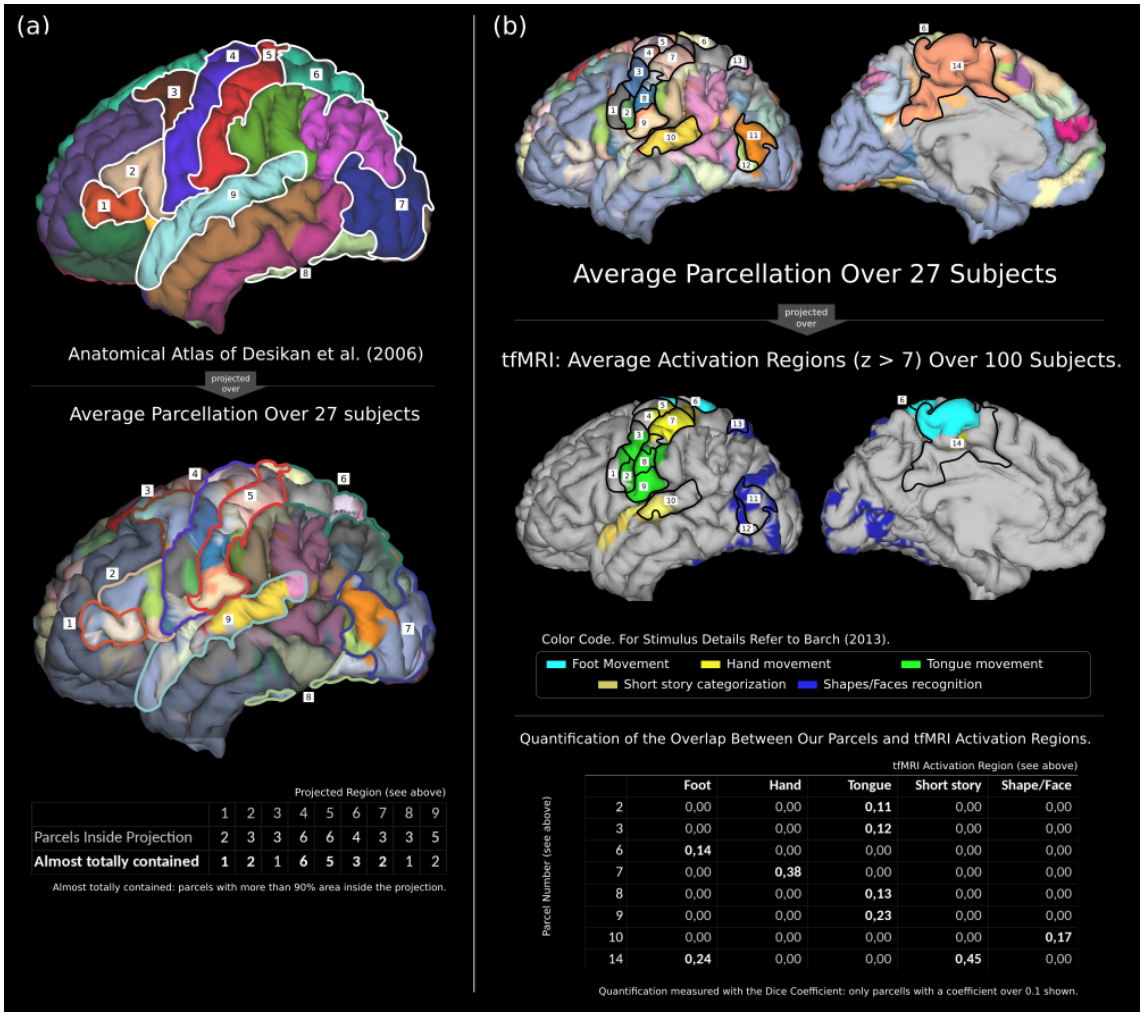

Figure 4: Comparison between a population-representative parcellation of 27 subjects; an anatomical atlas (Desikan 2006) and a functional study over the Unrelated100 HCP population.